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The performance of a size-structured stock assessment method in the face of spatial heterogeneity in growth

André E. Punt*

School of Aquatic and Fishery Sciences, University of Washington, Box 355020, Seattle, WA 98195-5020, USA

Abstract

Monte Carlo simulation is used to assess the performance of a size-structured stock assessment method of the type commonly employed to assess rock lobster populations in Australia and New Zealand. The simulations consider the impact of measurement error and process error in catchability and the length at 50% selectivity, as well as the implications of pooling data across populations that differ in terms of growth rate. The ability to estimate the virgin biomass depends critically on having catch-rate or size-composition data for earliest years of exploitation; in the absence of such data the estimates can be highly biased and imprecise. Several of the reference points commonly reported for assessment purposes (e.g. the biomass at which maximum sustainable yield is achieved) are, however, based on the estimate of the virgin biomass. Estimation performance (bias and precision of estimated quantities) deteriorates with increasing process error. For most of the scenarios examined, the expected benefits of increased precision arising from pooling data across spatial zones are not realized and better performance can be achieved by conducting assessments at the level of population and subsequently aggregating results spatially.

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1. Introduction

Fisheries for southern rock lobster (*Jasus edwardsii*) occur off New Zealand and the Australian States of South Australia, Victoria and Tasmania. Management advice for these fisheries is based on stock assessments, which involve fitting size-structured population dynamic models to catch, catch-rate and length–frequency data (e.g. Punt and Kennedy, 1997; Hobday and Punt, 2001; Breen et al., 2001; Bentley et al., 2001). All of these assessments are spatially structured to some extent. For example, the assessments in Tasmania are based on eight zones (Punt and Kennedy, 1997; Gardner et al., 2001; Fig. 1), those

in Victoria on two zones (Hobday and Ryan, 1997) and those in New Zealand on five zones (Annala and Sullivan, 2000). The frameworks used for the evaluation of fisheries policies for southern rock lobster off South Australia and western rock lobster off Western Australia are based on models that involve many spatial cells (Walters et al., 1993, 1998; McGarvey and Gaertner, 1999).

The evidence for spatial heterogeneity in rock lobster populations is strong, although this is perhaps not surprising given the very limited extent of movement of adult southern rock lobster inferred from tagging studies (e.g. Pearn, 1994). For this reason, the New Zealand, Victorian and Tasmanian assessments of southern rock lobster treat the populations within each zone as being independent of all the others. Nevertheless, given the long-lived and consequently highly

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* Tel.: +1-206-221-6319; fax: +1-206-685-7471.
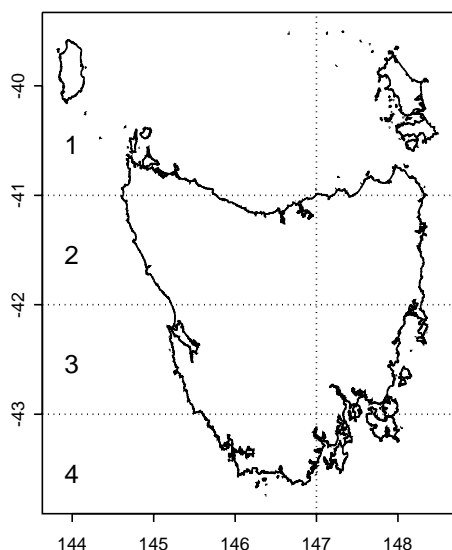*E-mail address:* aepunt@u.washington.edu (A.E. Punt).

Fig. 1. Tasmania, showing the eight statistical zones (modified from Punt et al. (1997)).

mobile pelagic larval stage (Booth, 1994; Booth and Phillips, 1994), it is unsurprising that no significant differences in allozyme frequencies have been found among southern rock lobsters sampled from Australia and New Zealand (Smith et al., 1980; Booth et al., 1990).

The boundaries among putative stocks when conducting assessments of southern rock lobsters have been selected, to the extent possible, on biological grounds. For example, the eight zones around Tasma-

nia were selected to account for spatial heterogeneity in growth rates, size at maturity, and fishing mortality, (Punt and Kennedy, 1997) as well as the spatial resolution of the data supplied in the past by fishers (S. Frusher, TAFI, pers. commun.). Nevertheless, the lack of sufficient data spatially (see Fig. 2 for the time-series of the number of animals sampled for length–frequency in the four zones to the east of Tasmania) means that the ability to correctly identify the boundaries (if indeed there is such a thing as a boundary) is problematic. One consequence of this is the tendency for 'stock' boundaries to be placed on lines of latitude and longitude.

Uncertainty regarding stock boundaries can lead to the data for several populations being combined for assessment purposes or those for one population being assessed as two (separate) populations. The first type of error can lead to serial depletion of some of the populations if fishing is not homogenous with respect to the populations in the group being assessed (International Whaling Commission, 1992; Fahrig, 1993). Nevertheless, given small sample sizes, the results of assessments based on data pooled spatially, although biased, may be usably precise. In contrast, unnecessarily sub-dividing a population reduces sample sizes and consequently decreases estimation precision. If management regulations are more conservative when uncertainty is greater, this can lead to resource under-utilization (e.g. International Whaling Commission, 1992). Furthermore, Butterworth and Geromont (2000) show that, under certain circumstances, unnecessarily sub-dividing a single
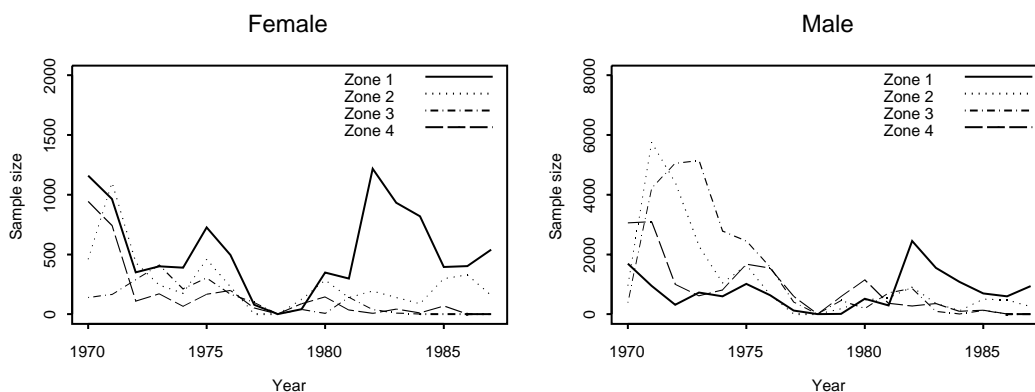

Fig. 2. Length–frequency sample sizes (1970–1987) for zones 1–4 (see Fig. 1).

homogenous population can also lead to biased estimates of key management related quantities.

Although size-based stock assessment methods are commonly applied to data for commercially valuable rock lobster and other populations, there are no published studies on the performance of such stock assessment methods. It should, of course, be recalled that only limited testing of age-based stock assessment methods based on the 'Integrated Analysis' paradigm has been conducted (Bence et al., 1993; National Research Council, 1998; Sampson and Yin, 1998; Punt et al., 2001), even though this paradigm forms the basis for the bulk of the quantitative stock assessments in Australia, South Africa and off the west coast of North America.

This paper therefore uses Monte Carlo simulation to evaluate the ability of a size-structured stock assessment method to estimate quantities of interest to management. This evaluation considers both deterministic (i.e. no error when sampling the population and no inter-annual fluctuations in catchability) scenarios as well as scenarios in which the data available for assessment purposes are subject to error. The errors considered include those related to making incorrect assumptions regarding spatial structure when conducting assessments using a size-structured stock assessment framework. The scenarios underlying the simulations are similar (but by no means identical) to that of assessing the rock lobster populations to the east of Tasmania (zones 1–4, Fig. 1). The study is based on a simple size-structured assessment framework consistent with the assessments for most rock lobster populations (at least in the southern Hemisphere) (e.g. Punt and Kennedy, 1997; Johnston, 1998; Hobday and Punt, 2001).

2. Methods

The steps in evaluating stock assessment methods using Monte Carlo simulation are summarized in Fig. 3 and are fully documented elsewhere (e.g. Kirkwood, 1981; de la Mare, 1986; Punt, 1988; Patterson and Kirkwood, 1995). In essence, Monte Carlo simulation involves the selection of a model (the operating model) to represent the truth for the simulations and the use of this model to generate pseudo data sets that could have arisen if the oper-
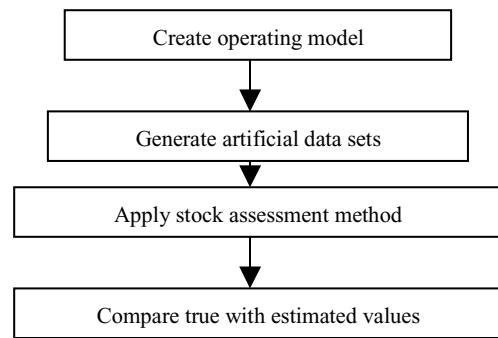

Fig. 3. Flowchart of the method used to evaluate the performance of stock assessment methods.

ating model was indeed real. The stock assessment method is then applied to each pseudo data set to produce estimates of the key stock assessment outputs and these are compared with the values for outputs from the operating model. Performance, in terms of estimating a quantity of interest to management (e.g. the egg production in a pre-specified year), is defined by the magnitude of the relative error:

$$E_t^{i,j} = 100 \times \frac{\hat{Q}_t^{i,j} - Q_t^{i,j}}{Q_t^{i,j}}$$

where $E_t^{i,j}$ is the relative error for quantity i during year t for simulation j, $Q_t^{i,j}$ the true (i.e. operating model) value for quantity i during year t for simulation j, and $\hat{Q}_t^{i,j}$ is the estimate of quantity i during year t for simulation j.

The relative errors for a given quantity could be summarized by a variety of statistics. These include the mean value (to quantify possible bias), the square root of the mean of the squared relative errors (i.e. the RMSE), the median and appropriate intervals of the relative errors, and the median of the absolute values for the relative errors. In this study, emphasis is placed on the median and 90% intervals for the relative errors and on the median of the absolute values of the relative errors (the MARE). The MARE rather than the RMSE is the focus of this study because it is less sensitive to outlying estimates. Such estimates (e.g. biomass estimates in the millions of tonnes) were observed to arise occasionally during the analyses. However, such estimates would be discounted during an actual assessment as being unrealistic.

2.1. The operating model

2.1.1. Overview

The operating model (see Appendix A for details) is size-, sex- and zone-structured. Natural mortality is assumed to occur throughout the year and fishing is assumed to occur during a pulse in the middle of the year. Growth occurs after fishing and natural mortality, but before settlement. There is no movement of animals among zones. Settlement occurs to the lowest size-class considered in the model (10 mm carapace width) and the model includes forty 6 mm size-classes. The annual settlement in a zone is related to the egg production generated from that zone by means of a Beverton–Holt stock–recruitment relationship, although for the bulk of the analyses settlement is assumed to be independent of egg production for consistency with the assumptions underlying most, but not all (e.g. Johnston (1998)), rock lobster stock assessments. The approach used to model annual settlement allows (if $\tau_r > 0$, see Eq. (A.3)) settlement to be correlated spatially. Table 4 of Punt et al. (1997) shows that the settlement of rock lobster for the zones to the west of Tasmania is positively correlated, as might be expected if settlement to these zones was governed by common environmental factors.

The operating model includes legal minimum lengths (LMLs) by sex, gear-selectivity (assumed to be of the logistic form) and discard mortality related to sub-legal animals. The catch by zone is calculated from the total catch across zones under the assumption that fishers distribute their catch in proportion to catch-rate. This assumption will definitely be violated for the rock lobster resource off Tasmania (M. Haddon, TAFI, pers. commun.), but is sufficient for the purposes of the analyses of this paper. Clearly, a far more sophisticated effort allocation model will be required if models are to be developed to predict the economic consequences of management actions.

Catchability is assumed to differ among zones in expectation and the annual differences in catchability from expectation are assumed to be correlated spatially. The annual selectivity pattern changes gradually over time through changes to the size at 50% selectivity and also due to inter-annual random variation in the size at 50% selectivity. Gradual changes in selectivity can be expected due to changes over time in fishing locations and market demand, whereas inter-annual

variation in selectivity can be attributed to the impact of environmental fluctuations.

The matrix that determines the fraction of animals (of a given sex and in a given zone) that grows from one size-class to another is based on the assumption that the expected growth increment is a linear function of size (negative expected growth increments are permitted). This is equivalent to assuming an underlying von Bertalanffy growth equation. The variance in growth increment is also a linear function of size, although a minimum value is placed on this variation to prevent unrealistically small (or negative) variation for large animals.

The initial conditions correspond to a population at pre-exploitation equilibrium (year 1), and the ratio of the egg production in the final (50th) year to the pre-exploitation equilibrium egg production (the current depletion) is pre-specified. This ratio is pre-specified for each set of simulations, because it was expected from previous studies (e.g. Punt, 1988; Punt et al., 2001) that the performance of the assessment method would be sensitive to the current depletion of the resource.

It should be noted that, although the operating model is relatively complicated, several potentially important factors from the viewpoint of fisheries management (regulations on the landing of berried females, within-season dynamics, multiple fishing sectors, changes over time in LMLs and escape gap regulations, etc.) are ignored. Incorporating such factors should not, however, impact upon the qualitative conclusions of this paper.

2.1.2. Parameterization

The values for the bulk of the parameters of the operating model (e.g. those related to selectivity, natural mortality and egg production) are based on those chosen for previous assessments of Tasmanian rock lobster (Punt and Kennedy, 1997; Gardner et al., 2001). The values for the parameters that determine the size-transition matrix are selected so that the size-distributions at pre-exploitation equilibrium (Fig. 4) are very similar to those derived for Tasmanian rock lobster by Punt et al. (1997). The values for the parameters that determine the extent of variability in the various modeled processes cannot be determined from the results of past assessments and are therefore set to 'realistic' values (Table 1). Sensitivity
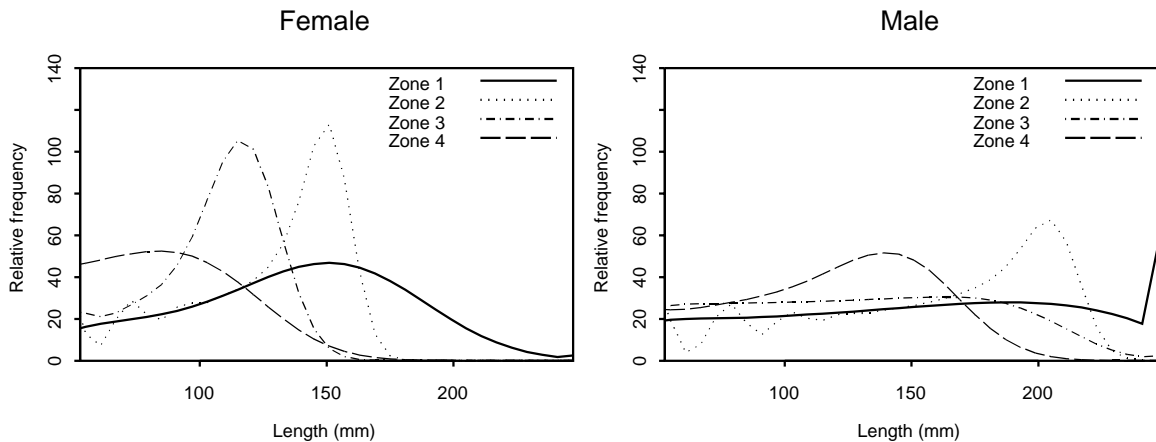
Fig. 4. Size–frequency distributions at pre-exploitation equilibrium for zones 1–4 (greatest to smallest asymptotic size).

tests consider varying the values for some of these parameters.

The catch series on which the calculations are based (Fig. 5) is hypothetical but captures the tendency of catches of rock lobster populations to increase rapidly, peak and then decline to lower levels. The base-case choice for the current depletion of the resource is 0.3 (this value falls within the range of estimates of current depletion for the stocks of rock lobster assessed

using size-structured models in Australia and New Zealand). Sensitivity is explored by setting the current depletion to 0.05 (highly depleted population) and 0.7 (under-utilized population).

2.1.3. Data generation

The data available for assessment purposes are catches (assumed to be known exactly), catch-rates and length–frequency data (commercial and scientific sampling). Tagging data (1000 recaptures per sex) are assumed to be available to estimate the size-transition matrix. Appendix A.8 outlines the technical details of how these data are generated. The sample sizes by year for length–frequency data (Table 2) were chosen to mimic roughly the actual pattern for rock lobster off Tasmania. The base-case analyses assume equal sample sizes in each zone, although sensitivity tests consider more realistic alternatives.

It is necessary to pool data across zones when assessments are conducted based on an area that consists of more than one zone. This is straightforward for the catches because they are simply added together. The pooled catch-rates are obtained by catch-weighting the catch-rates by zone and the pooled length–frequency data are obtained by adding the length–frequency samples by zone. The latter assumption may be surprising because a more ideal approach would seem to be to catch-weight the length–frequency data (and this is examined in one of the tests of sensitivity). However, the base-case assumption has been made because, if it was

Table 1
The base-case values for the parameters related to sources of variability and discard mortality[a]

Quantity	Value
Settlement	
Overall variation, σ_r	0.6
Spatial correlation, τ_r	0.5
Catchability	
Variation among zones, σ_ϕ	0.2 (0.4)
Inter-annual variation, σ_φ	0.2 (0.4)
Correlation among zones, τ_φ	0.71
Size at 50% selectivity	
Variation in gradual changes, σ_δ	0 (2, 4)
Inter-annual variation, σ_η	0 (4, 8)
Pre-exploitation settlement	
Variation among zones, σ_μ	0.4
Spatial correlation, τ_μ	0
Discard fraction, Ω	0.1

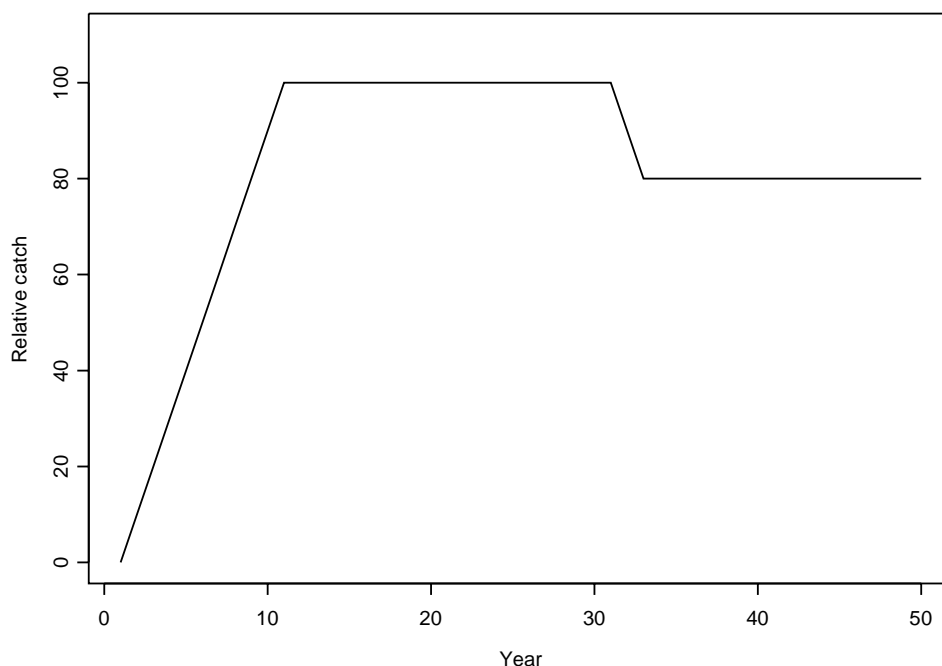[a] The values for the sensitivity tests are given in parenthesis.

Fig. 5. The assumed catch history.

not known that the zones being pooled contained separate populations, the length–frequency sample collected would be assumed to be random with respect to the population.

Table 2
The length–frequency sample sizes[a]

Scenario (years)	Zone			
	1	2	3	4
Base-case				
21–38	600	600	600	600
39–50	1200	1200	1200	1200
Alt l/f sample 1				
11–17	500	500	500	500
23–27	1500	1500	1500	1500
43–50	3500	3500	3500	3500
Alt l/f sample 2				
11–17	300	300	300	300
23–27	200	200	200	200
43–50	600	600	600	600
Lower l/f sample sizes				
21–38	1000	200	200	100
39–50	2000	400	400	2000

[a] Catch-rates are available for years 21–50.

2.2. The size-structured stock assessment method

The stock assessment involves two steps: estimating the size-transition matrix and fitting the size-structured population dynamics model[1]. The former involves estimating the values for the parameters of the growth model ($\tilde{a}$, $\tilde{b}$, the minimum standard deviation, and a length-independent growth increment coefficient of variation) by minimizing the following objective function:

$$-\ln L = \sum_i \left(0.5 \ln(\hat{\sigma}_i^2 + \sigma_{\mathrm{obs}}^2) + \frac{(L_i - \hat{L}_i)^2}{2(\hat{\sigma}_i^2 + \sigma_{\mathrm{obs}}^2)^2} \right) \tag{1}$$

where L_i is the observed length at recapture for the ith animal, $\hat{L}_i$ the growth model-predicted length at recapture for the ith animal, $\hat{\sigma}_i$ the growth model-predicted growth increment standard deviation for the ith animal, and σ_{obs} the level of measurement error.

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[1] The AD Model Builder package (© Otter Software) was used for both estimation steps.

The model predictions are determined from Eqs. (A.15) and (A.18), except that CV_2 in Eq. (A.15) is assumed to be zero, and σ_{obs} is assumed to be known exactly (this would be estimated by comparing the recorded lengths at release and recapture from within-season recaptures (P. Breen, NIWA, pers. commun.)).

The parameters of the size-structured population dynamics model (and hence the values for the quantities of management interest) are computed by maximizing a likelihood function involving the catch-rate and the length–frequency data. Ignoring constants independent of the model parameters, the quantity minimized is

$$-\ln L = n_c \ln(\hat{\sigma}_q + 0.01)$$
$$+ W \sum_s \sum_l \sum_y \frac{(\rho_{t,l}^s - \hat{\rho}_{t,l}^s)^2}{\rho_{t,l}^s(1 - \rho_{t,l}^s) + 1/40} \quad (2)$$

where n_c is the number of years for which catch-rates are available (years 21–50), $\hat{\sigma}_q$ the maximum likelihood estimate for the variation in catchability:

$$\hat{\sigma}_q^2 = \frac{1}{n_c} \sum_t \{\ln U_t - \ln \hat{U}_t\}^2 \quad (3)$$

U_t is the observed catch-rate for year t, $\hat{U}_t$ the model-predicted catch-rate for year t, $\rho_{t,l}^s$ the observed fraction that animals in size-class l constitute the catch (in number) of animals of sex s during year t, $\hat{\rho}_{t,l}^s$ the model-predicted fraction that animals in size-class l constitute the catch (in number) of animals of sex s during year t, and, W the weight (the effective sample size assumed to be 100) assigned to length–frequency data.

The 0.01 is added to $\hat{\sigma}_q$ to increase robustness (to prevent the model from choosing recruitments to mimic the catch-rate data exactly). The form of the likelihood function for the length–frequency data is a variant of the robust likelihood formulation developed by Fournier et al. (1998), in which the variance is based on the observed rather than the predicted fractions (Starr et al., 1999; Bentley et al., 2001).

The size-structured model is identical to the operating model except that only a single zone is considered and all sources of variation except recruitment variability are ignored. The only parameters (other than

the nuisance parameters) estimated are the annual settlements, which are parameterized as follows:

$$R_t = \bar{R}\, e^{\varepsilon_t} \quad (4)$$

where R_t is the settlement during year t, $\bar{R}$ the mean settlement, and ε_t the settlement residual for year t.

A penalty $(1/(2(0.4)^2))\sum_t \varepsilon_t^2$ is added to the objective function minimized to further stabilize the estimator. This penalty is equivalent to assuming that settlement is log-normally distributed with a coefficient of variation of 40%.

2.3. The quantities of management interest considered

The quantities for which results are presented:

(1) the time-series of egg production (Eq. (A.4));
(2) the time-series of legal fishable biomass in the middle of the year (Appendix A.6);
(3) the time-series of annual settlement;
(4) the time-series of annual recruitment to the fishery (Eq. (A.16)).

3. Results and discussion

3.1. Deterministic results

Fig. 6 shows the time-trajectories of the medians and 90% intervals for the relative errors for the four time-series for zone 1 (fastest growth) for the case in which the estimator is provided with deterministic data (no measurement error) and catchability does not exhibit inter-annual fluctuations (i.e. $\sigma_\varphi = 0$). The estimates of fishable biomass, egg production and surplus production provided by the stock assessment method are, as expected, essentially identical (relative errors $\sim 0.1\%$) to the true values for the years for which data are available (years 21–50). This is, however, not the case for the time-series of settlements and for estimates of all four quantities for the years prior to year 21. This may seem surprising, given that the assessment model is identical to the operating model. It arises because, in the absence of data for years 1–20 and the constraint being placed on the recruitment residuals, the stock assessment model sets most of the settlements for the years before year 21 to the
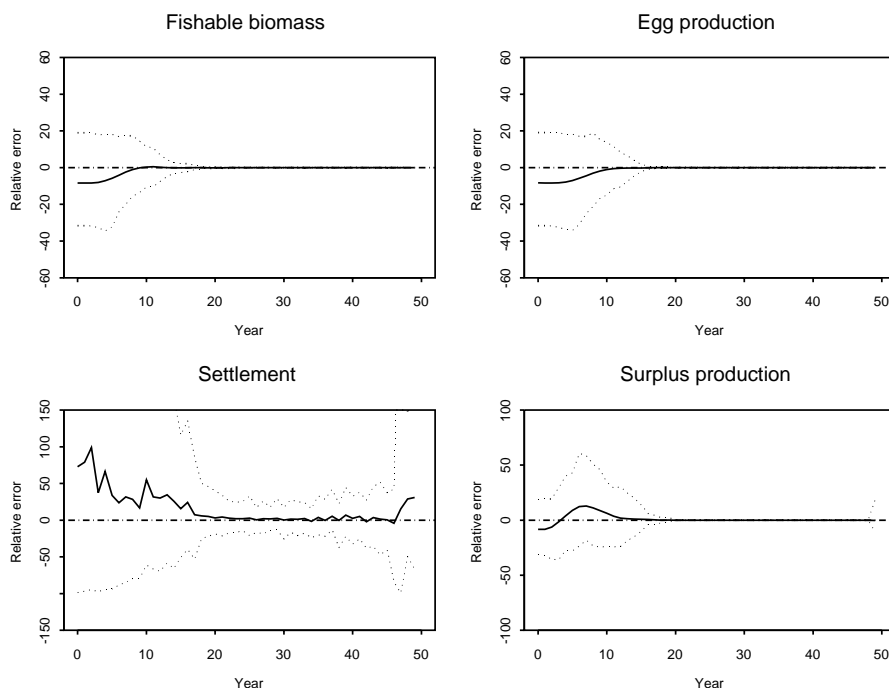
Fig. 6. Medians and 90% intervals for relative errors for zone 1 for the base-case scenario in the absence of measurement error and inter-annual variability in catchability.

average settlement for years 21–50. However, settlement in the operating model is not constant over years 1–20. The result that it is not possible to estimate the initial biomass even with deterministic data suggests that basing management advice on the ratio of the current biomass (or egg production) to that in a virgin (or pre-exploitation) state, although common (e.g. Bentley et al., 2001; Hobday and Punt, 2001), is questionable. Punt et al. (2001) reached a similar conclusion for fish species in Australia's South East Fishery. As expected, uncertainty in settlement is greatest for the year classes that settled before the start of the data series and for those that have just entered the fishery.

The results in Fig. 6 pertain to the application of the stock assessment method to a single zone (the results for the other zones are qualitatively identical to those in Fig. 6). Fig. 7 shows results for two of the time-series (fishable biomass and surplus production) for zone 1 and for combinations of zones. The results for assessments based on zones 1 and 2 combined and 3 and 4 combined are close to unbiased for years

21+. However, this is not the case if data for all four zones are pooled, which results in a negative bias of approximately 5% (fishable biomass) and 15% (surplus production).

Fig. 8 shows results of assessments, in which the width of each size-class is increased from 6 to 12 mm. The data are again deterministic. However, now there is negative bias for the years after year 20, even when the estimator is applied to data for zone 1 under the assumption that the boundary between zones 1 and 2 is correctly placed. The assessments of rock lobster populations off southern Australia have been based on a range of size-class widths, e.g. 2 mm (Punt and Kennedy, 1997) and 5 and 10 mm (Hobday and Punt, 2001), with the width generally being based on computational convenience. The results in Fig. 8 suggest a need to consider sensitivity to the width assumed for the size-classes when conducting assessments using size-based models. Such sensitivity has not been examined to date in assessments of southern rock lobster.
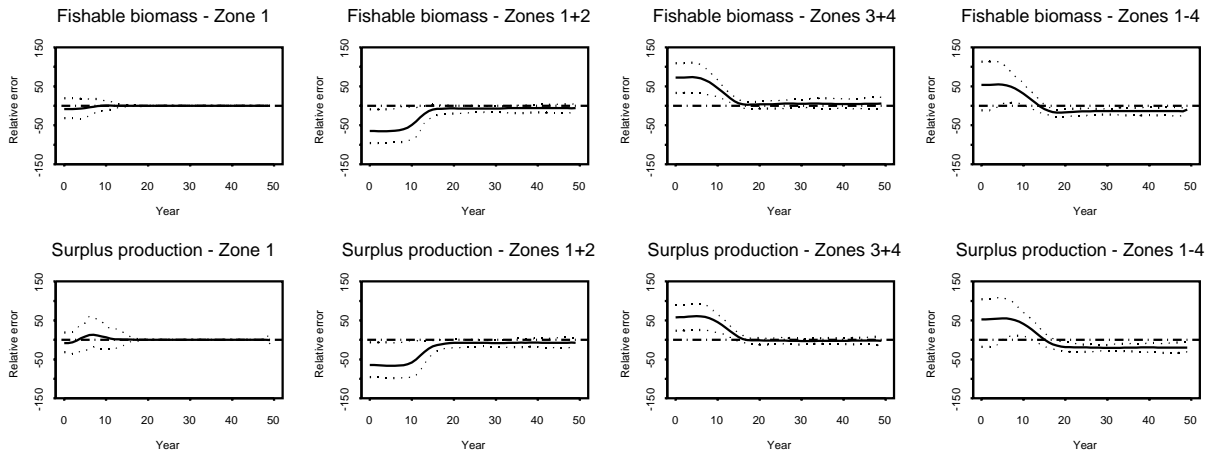
Fig. 7. Medians and 90% intervals for relative errors for zone 1 and combinations of zones for the base-case scenario in the absence of measurement error and inter-annual variability in catchability.

3.2. Stochastic results

Figs. 9 and 10 show time-trajectories of the distributions of relative error for the case in which there are inter-annual fluctuations in catchability and the data supplied to the stock assessment method are subject to measurement error. The results in Fig. 9 are based on assessments that are provided with the true size-transition matrix and those in Fig. 10 are based on assessments that estimate the size-transition matrix using the tagging data (see Section 2.2).

The results in Figs. 9 and 10 are qualitatively identical to those in Fig. 7, except that the widths of the intervals are broader (particularly for the years prior to year 21) and performance for the most recent year is less than perfect. As expected, the distributions of relative error are wider when the assessment is based on data with measurement error and these distributions are still wider when the size-transition matrix is also uncertain.

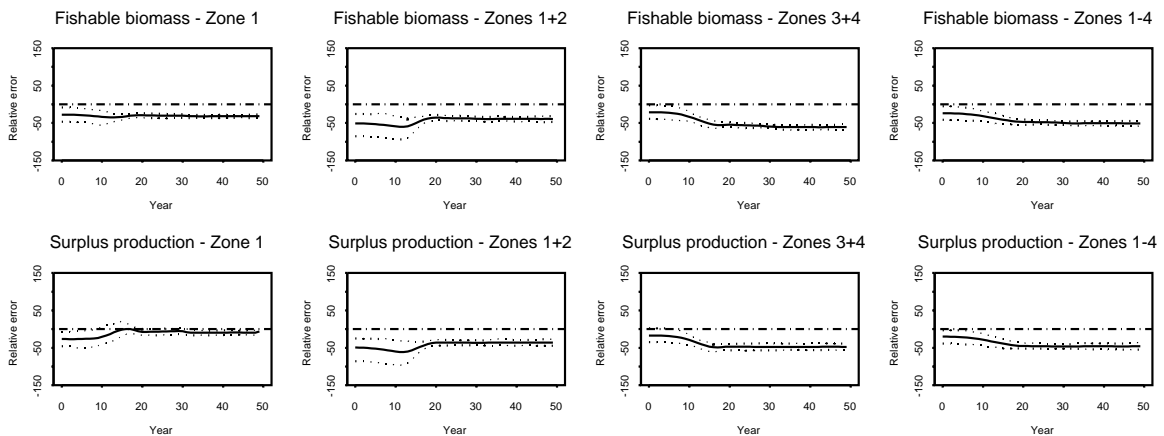Table 3 lists the bias (average relative error) and MARE (median of the absolute values of the relative

Fig. 8. As for Fig. 7, except that the size-classes assumed when conducting assessments are assumed to be 12 mm rather than 6 mm.
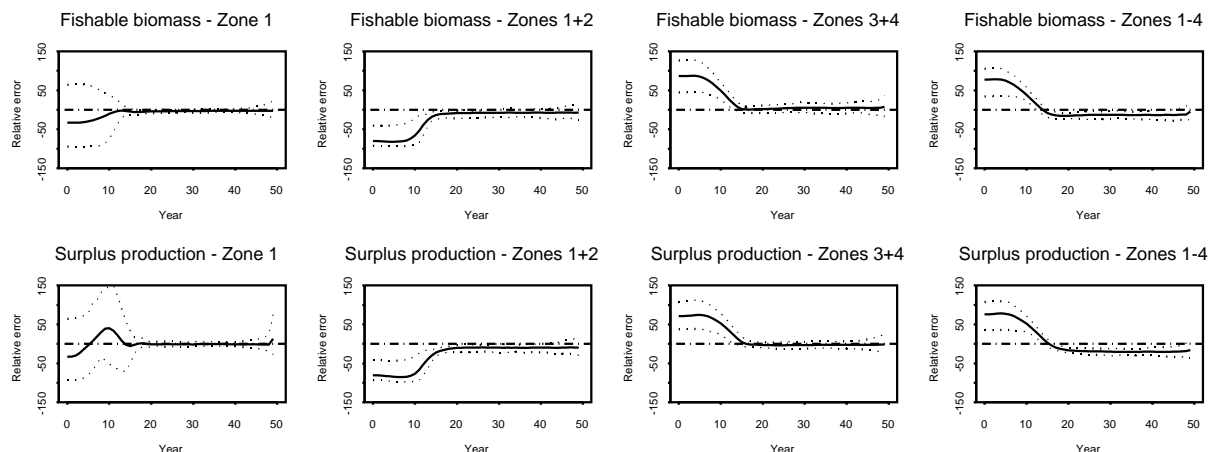
Fig. 9. As for Fig. 7, except that the catch-rate and length–frequency data are subject to observation error.

errors) for the fishable biomass in the first year (essentially the virgin biomass) B_1, the fishable biomass in the last year B_{50}, and the ratio of the fishable biomass in the last year to that in the first year for which catch-rate data are available B_{50}/B_{20}. The results in Table 3 pertain mainly to zone 2 (chosen because it is bordered by two zones unlike zone 1). The default specifications for the scenarios in Table 3 correspond to those underlying Fig. 10 (i.e. process error in catchability, measurement error in the length–frequency data and the values for the size-transition matrix estimated from the tagging data; henceforth referred to as the base-case scenario). This scenario should, however, be considered close-to-ideal as there is no process error

in the size at 50% selectivity and the length–frequency sample sizes are very large.

As expected from Fig. 10, the bias for B_1 is negative and there is large uncertainty associated with this estimate. The bias and MARE for the other two quantities are much smaller. The bias in B_1 becomes increasingly negative as the growth rate is reduced (compare the results for zones 1–4 in Table 3a). The estimates of B_1 become increasingly negatively biased as allowance is made for process error in the size at 50% selectivity (see the rows in Table 3a for which $\sigma_\delta > 0$) and the MAREs for all quantities increase (as expected) when this additional source of uncertainty is introduced. Increasing the extent of variation in
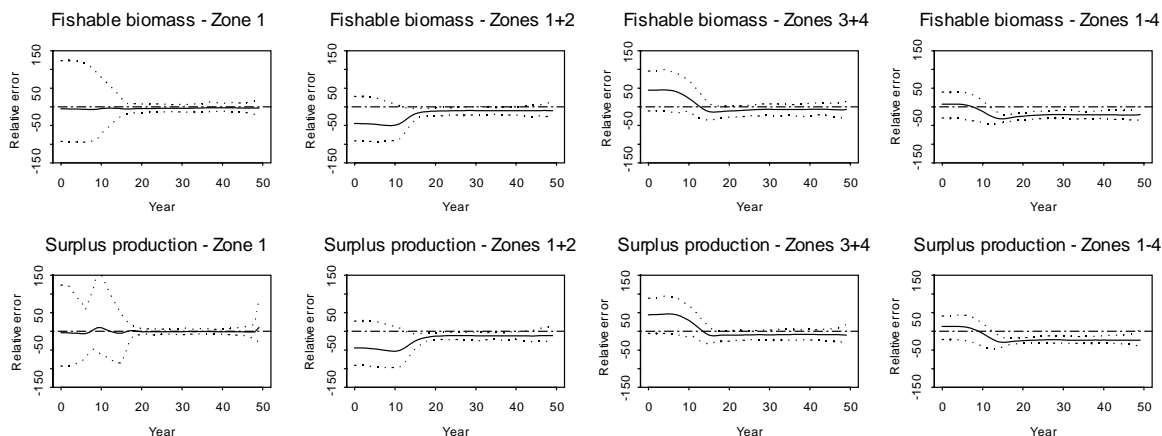

Fig. 10. As for Fig. 9, except that the growth transition matrix is estimated rather being known exactly.

Table 3
Bias and median absolute relative errors (MARE) for fishable biomass for zone 2 for the base-case analyses and various sensitivity tests

Analysis	B_1		B_{50}		B_{50}/B_{20}	
	Bias	MARE	Bias	MARE	Bias	MARE
(a) Modifications to the structure of the operating model						
Base-case	−20.4	37.4	3.4	8.6	4.4	8.5
Zone 1	−5.5	59.0	−3.5	11.2	1.3	8.2
Zone 3	−35.4	54.7	−1.5	12.3	2.2	11.5
Zone 4	−44.9	58.1	−3.3	10.8	−0.7	8.8
$\sigma_\eta = 4$	−20.1	47.0	3.5	10.1	4.0	9.6
$\sigma_\eta = 4$; $\sigma_\delta = 2$	−22.9	47.6	−0.4	12.0	−0.8	12.1
$\sigma_\eta = 8$; $\sigma_\delta = 4$	−35.6	48.4	−4.6	17.7	−9.1	15.8
$\sigma_\phi = 0.4$	−18.1	40.4	3.3	8.5	3.7	8.7
$\sigma_\varphi = 0.4$	−18.8	37.8	4.0	16.7	4.5	16.9
Initial depletion = 0.05	−21.2	37.8	25.0	8.7	44.9	17.4
Initial depletion = 0.7	−17.0	53.1	6.4	11.3	1.3	6.8
Steepness = 0.75	−19.5	39.0	3.1	9.2	3.3	9.3
Overlap between zones 1, 2 and 3	−42.8	52.8	17.5	16.1	1.4	9.8
$\sigma_\eta = 8$; $\sigma_\delta = 4$; $\sigma_\varphi = 0.4$	−35.4	54.9	−9.1	22.4	−13.2	21.5
(b) Alternative data collection/analysis strategies						
Base-case	−20.4	37.4	3.4	8.6	4.4	8.5
Alt l/f sample 1	−3.3	7.6	2.6	10.4	3.4	9.6
Alt l/f sample 2	−6.0	8.3	−0.6	10.1	2.7	9.4
Lower l/f sample sizes	−39.8	41.3	−0.8	9.5	1.6	8.7
Lower tag numbers	−17.3	70.2	2.6	10.2	4.0	8.8
With scientific l/f data	−20.5	39.6	−2.5	6.7	−2.0	7.4

average catchability, σ_ϕ, among zones has very little impact on estimation performance. In contrast, the MAREs for B_{50} and B_{50}/B_{20} almost double when the extent of process error in catchability is increased from $\sigma_\varphi = 0.2$ to $\sigma_\varphi = 0.4$, which further highlights the well-known importance of having a reliable index of abundance when conducting stock assessments.

The MARE for B_{50}/B_{20} when the depletion in year 50 is 0.05, is higher than for the base-case scenario for which this depletion is 0.3 (the biases for this scenario should be ignored as there were a few outlying estimates). The ability to estimate B_1 and B_{50} is poorer when the depletion in year 50 is 0.7, although this is not unexpected given the lesser contrast in the catch-rate series in this case. The estimation of biomass is not very sensitive to steepness, being 0.75 rather than 1, although this would not necessarily be the case for projections into the future. There is little impact on the MARE for B_{50}/B_{20} if an assessment is conducted in which 10% of the data for zone 1 and 10% of the data for zone 3 are included in the assessment of zone 2 (row 'overlap between zones 1, 2 and

3' in Table 3a), whereas the bias associated with B_{50} increases (which is not surprising given that the assessment contains data for more than just zone 2). What is unexpected is that the negative bias for B_1 becomes larger when the assessment includes data from zones 1 and 3 as well as from zone 2. This must be a consequence of model mis-specification arising from combining data from populations with different dynamics.

The largest impact on performance in Table 3a appears to be related to process error in the size at 50% selectivity and additional process error in catchability. Fig. 11 shows distributions of relative error for B_1, B_{50} and B_{50}/B_1 for the base-case scenario and for the scenario in which $\sigma_\varphi = 0.4$, $\sigma_\eta = 8$ and $\sigma_\delta = 4$. The sizeable number of large negative relative errors for B_1 warrants further attention. Fig. 12, therefore, shows the fit to the catch-rate data and the estimated time-series of settlements for one of the simulations for the base-case scenario. At face value, the fit to the catch-rate data appears adequate and the time-sequence of annual settlements appears a priori plausible. The high settlements between years 1 and
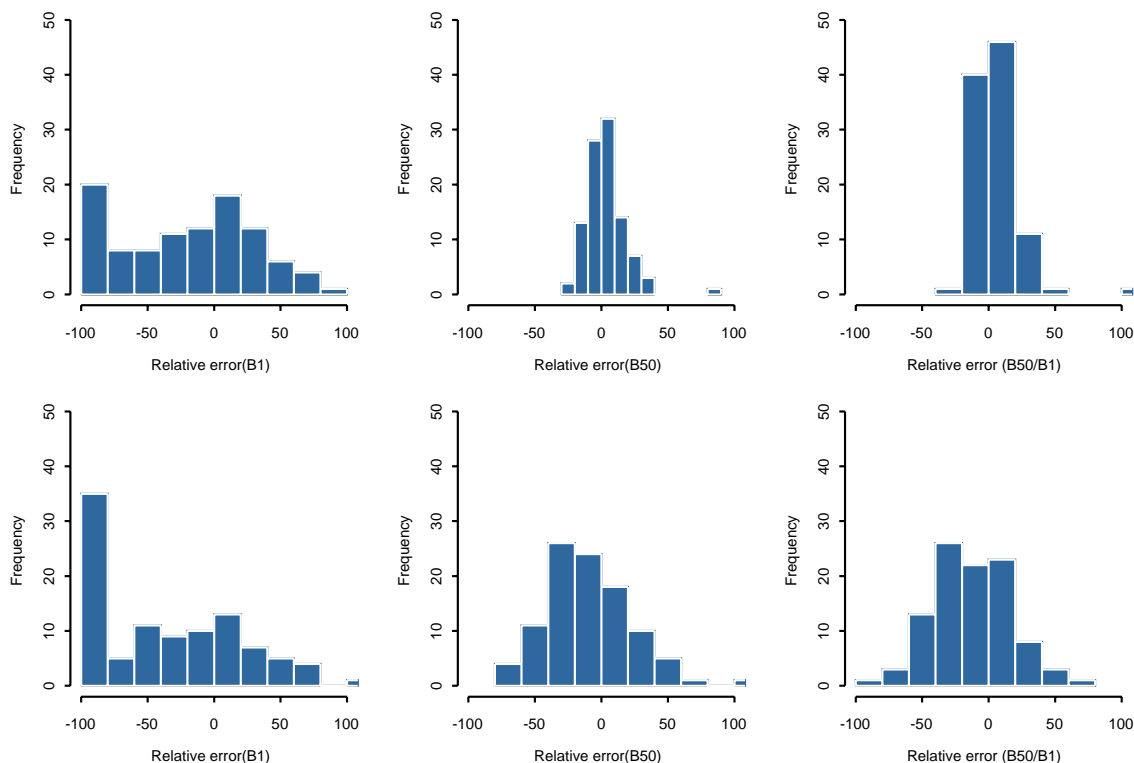
Fig. 11. Distributions of relative error (expressed as a percentage) for three quantities for the base-case scenario (upper panels) and the '$\sigma_\varphi = 0.4$, $\sigma_\eta = 8$ and $\sigma_\delta = 4$' sensitivity test (lower panels).

10 arise presumably to fit some aspect of the early length–frequency data. However, the consequence of these high settlements for the fishable biomass is that there was a marked increase in fishable biomass from

years 10–20. The behavior of the estimator in this case is clearly unacceptable, given the known truth. It is not entirely clear, however, that the trajectory of fishable biomass in Fig. 12 would automatically be
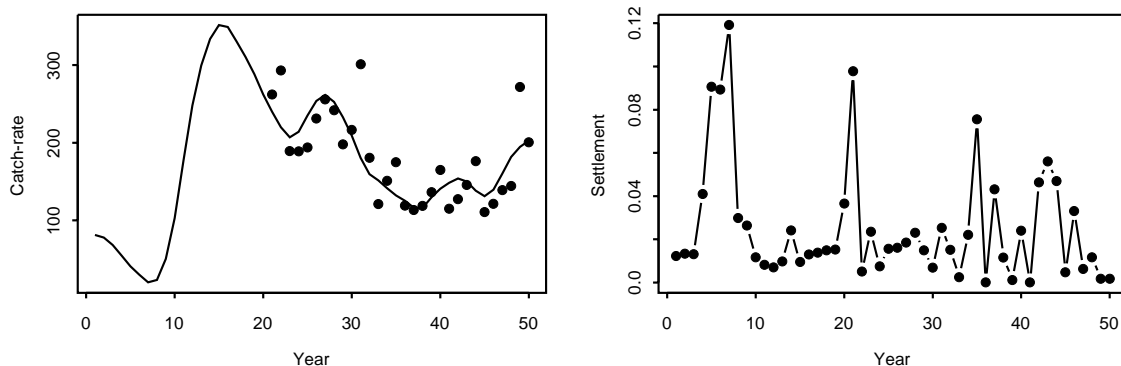

Fig. 12. Observed (solid dots) and model-predicted (solid lines) catch-rates (left panel), and model-predicted settlement (right panel). The results are for a single simulation for the base-case scenario.

considered implausible in an actual assessment. For example, given the catches in Fig. 5, it might be argued that the fishery be built up along with the fishable biomass.

Table 3b examines performance when the data available for assessment purposes are modified from the base-case assumptions (see Table 2 for details related to the sample sizes for length–frequency). Conducting assessments when there are length–frequency (but not catch-rate) data for years 11–17 improves the ability to estimate B_1 markedly (a reduction from a MARE of 37.4 to only 7.6%). This result highlights the considerable value of attempting to identify length–frequency data for the early years of the fishery as this constrains the estimates of biomass. As expected, lower length–frequency sample sizes (200 rather than 600 for zone 2) lead to slightly higher MAREs. The increases in MARE are, however, not particularly substantial because a sample size of 200 is relatively large anyway. At this level of sample size, estimation performance is still dominated by process error in catchability rather than measurement error in the length–frequency data.

Reducing the number of animals from which the size-transition matrix is estimated from 1000 to 200 leads to increased MAREs, particularly for B_1 (row 'lower tag numbers' in Table 3b). The latter probably occurs because, with a lower sample size, it becomes

very difficult to obtain sufficient animals to quantify the growth of large animals adequately. Basing the length–frequency data, on scientific rather than commercial sampling for years 39–50 (as is the case in reality for southern rock lobster off Tasmania) leads to slightly lower MAREs for B_{50} and B_{50}/B_{20}.

3.3. Comparing pooled and non-pooled assessments

Table 4 compares estimates of biomass (in years 1, 40 and 50) and year 50 depletion (relative to years 1 and 20) for populations aggregated across zones. The results are reported as the difference between the MARE for assessments in which the data are pooled across zones and those in which the results from zone-specific assessments are combined. A positive number in Table 4 indicates that conducting assessments by zones prior to combining leads to lower MAREs.

The most notable feature of Table 4 is the large number of positive numbers. For assessments of the populations in zones 1 and 2 combined, there is a very strong preference for separate assessments. This preference is not nearly as strong for zones 3 and 4 and all zones combined when the assessment based on pooled data leads to better estimates for B_1 and B_{50}/B_1. However, the results in Table 3 and Fig. 10 indicate that the

Table 4

Difference in median absolute relative errors (MARE) for fishable biomass between analyses which combine zones and those which add results for the component zones for three combinations of zones for the base-case analyses and various sensitivity tests

	Zones $1 + 2$					Zones $3 + 4$					Zones $1 + 2 + 3 + 4$				
	B_1	B_{50}	B_{40}	B_{50}/B_1	B_{50}/B_{20}	B_1	B_{50}	B_{40}	B_{50}/B_1	B_{50}/B_{20}	B_1	B_{50}	B_{40}	B_{50}/B_1	B_{50}/B_{20}
Base-case	27	6	6	77	0	−10	3	3	−60	0	−20	10	11	−11	0
$\sigma_\eta = 4$	40	5	6	233	3	15	1	4	−1	2	−30	12	13	−30	1
$\sigma_\eta = 4; \sigma_\delta = 2$	50	2	3	290	−2	16	−1	5	−6	−1	−31	11	12	−40	0
$\sigma_\eta = 8; \sigma_\delta = 4$	33	3	5	201	−1	28	0	3	−5	−5	−34	8	9	−62	−2
$\sigma_\phi = 0.4$	16	8	9	23	2	−3	5	4	−47	1	−18	9	13	−5	1
$\sigma_\varphi = 0.4$	27	6	7	85	1	−8	3	3	−58	1	−20	9	12	−13	0
Initial depletion $= 0.05$	2	1	4	10	4	6	4	2	−11	7	−1	−2	11	−4	16
Initial depletion $= 0.7$	44	14	14	749	1	−38	5	8	−56	0	−39	17	19	−72	0
Alt l/f sample 1	32	6	8	40	3	0	3	4	−2	0	11	10	12	3	0
Alt l/f sample 2	36	7	7	48	2	−2	4	4	−5	−1	9	10	12	2	1
Lower l/f sample sizes	11	5	7	2	2	33	4	5	679	1	4	8	11	8	3
Lower tag numbers	39	2	4	109	1	1	3	3	−10	−1	−29	9	10	−26	2
$\sigma_\eta = 8; \sigma_\delta = 4;$ $\sigma_\varphi = 0.4$	30	6	6	134	−1	22	−2	3	1	−6	−33	6	9	−38	3
With survey l/f data	30	8	4	119	2	−9	5	2	−55	1	−20	11	7	−10	1

MAREs for these quantities are generally very high so the improvements due to pooling still do not result in particularly usable estimates. Therefore, the results in this paper suggest that conducting assessments at small spatial scales (with the consequent smaller sample sizes) is preferable to conducting assessments pooling data across putative stocks, at least when the amount of data for assessment purposes is similar to that considered in this study.

3.4. General discussion

The results of this study highlight the value of estimating the performance of stock assessment methods when the data are deterministic, because it allows the impact of structural error to be distinguished from that of measurement error. If a stock assessment method cannot estimate a quantity of management interest reliably when the data are deterministic, there is no reason to anticipate that it will perform well at estimating that quantity when the data are subject to measurement error.

The inability to estimate the initial biomass (which in this case is also the average pre-exploitation biomass, B_{virg}) questions the common practice of defining management reference points in terms of the ratio of the most recent biomass to the biomass in some early year (or B_{MSY}, which is just a multiple of B_{virg}). In principle, it might have been possible to estimate B_{virg} directly from the time-series of settlements. In fact, for the example in Fig. 12, the estimated average settlement is roughly 25% greater than the actual average settlement. Therefore, in this case, the ratio B_{50}/B_{virg} would have been substantially closer to the true value of B_{50}/B_1 than the actual estimate of the ratio B_{50}/B_1 had B_{virg} been based on multiplying the fishable biomass-per-settlement by the average settlement. The use of average settlement to define the virgin biomass, however, ignores any stock-recruitment relationship. Although this assumption is correct for the bulk of the analyses of this paper (and may even be correct in general for rock lobster populations), it is not necessarily true; use of average settlement over a period during which the spawner biomass declines may lead to positively biased estimates of current depletion.

Although, the stock assessment method examined this paper forms the basis for actual assessments of rock lobster populations, it is by no means the only way to conduct size-based modeling. In particular, future studies along the lines of this paper need to examine the performance of estimators that include some of the features in the most recent assessment of southern rock lobster off New Zealand (Bentley et al., 2001), namely estimation of the selectivity pattern, the maturity ogive and the size-transition matrix simultaneously with the other model parameters.

Although this paper has focused on the ability to estimate quantities of interest to management, there is an increasing trend to manage rock lobster populations using decision rules (or management procedures) (Starr et al., 1997; De Oliveira et al., 1998; Geromont et al., 1999). Future simulation studies will need to consider the performance of decision rules in terms of how well they satisfy the objectives for management. Such an evaluation is, however, beyond the scope of this paper because, for instance, it depends on having a model of how fishers distribute their effort spatially in response to changes in fisheries regulations. Work along these lines is, however, currently being undertaken (M. Haddon, TAFI, pers. commun.) for the southern rock lobster resource off Tasmania.

Finally, it should be noted that although the errors evident in Figs. 6–12 are large, they nevertheless under-estimate the true extent of uncertainty. This is because the analyses of this paper are based on the assumptions that the average selectivity pattern, the rate of discard mortality and the rate of natural mortality are known. The analyses are also based on the assumption that form of the growth curve and the relationship between catch-rate and abundance are known. In contrast, there is likely to be considerable uncertainty about the form of the growth curve, the relationship between catch-rate and abundance, and the values for selectivity, natural mortality and discard mortality in any real case.

Appendix A. The operating model

A.1. Basic dynamics

The equation which specifies the number of animals of sex s in size-class l at the start of year $t+1$ in zone k, takes account of natural mortality, fishing mortality, growth and recruitment:

$$N_{t+1}^{l,s,k} = \sum_{l'} X_{l,l'}^{s,k} N_t^{l',s,k} \, e^{-M} (1 - F_t^k S_{l',t}^s (V^{l',s} + \Omega(1 - V^{l',s}))) + R_t^{l,s,k} \quad \text{(A.1)}$$

where $N_t^{l,s,k}$ is the number of animals in zone k of sex s in size-class l at the start of year t, $X_{l,l'}^{s,k}$ is, for zone k, the fraction of animals of sex s in size-class l' which grow into size-class l at the end of the year (i.e. after mortality), M the annual instantaneous rate of natural mortality (assumed to be independent of zone, sex and size and equal to 0.1 per year see Punt and Kennedy (1997) for details), $S_{l',t}^s$ the selectivity of the fishing gear on animals of sex s in size-class l' during year t (assumed to be independent of zone), Ω the fraction of the catch of sub-legal animals that die (or are landed illegally), $V^{l,s}$ is the fraction of the catch of animals in size-class l and of sex s that can be landed legally:

$$V^{s,l} = \begin{cases} 0 & \text{if } L_l + \Delta L \leq \text{LML}^s \\ \dfrac{L_l + \Delta L - \text{LML}^s}{2\Delta L} & \text{if } L_l - \Delta L < \text{LML}^s \\ & \quad < L_l + \Delta L \\ 1 & \text{if } L_l - \Delta L \geq \text{LML}^s \end{cases} \quad \text{(A.2)}$$

L_l is the average of the upper and lower limits of size-class l, ΔL the half the width of a size-class (3 mm), LML^s the legal minimum length (104 mm for females and 110 mm for males), F_t^k the exploitation rate in zone k during year t on fully selected (i.e. $S_{l,t}^s = 1$) animals, and $R_t^{l,s,k}$ the settlement in zone k of animals of sex s into size-class l at the end of year t (see Appendix A.2).

The fraction of animals in size-class l and of sex s that can be landed legally is zero if the upper bound of the size-class is below the minimum legal size and unity if the lower bound of the size-class is above the minimum legal size; otherwise it is the fraction of the size-class above the minimum legal size.

A.2. Settlement

The settlement in zone k during year t is defined as the number of animals that reach the smallest size considered in the model, l_1 (taken in this model to be 10 mm) that year:

$$R_t^{l,s,k} = \begin{cases} \dfrac{R_0^k (\text{SB}_t^k / \text{SB}_0^k)}{\alpha + \beta(\text{SB}_t^k / \text{SB}_0^k)} \, e^{\varepsilon_t^k - \sigma_r^2/2} & \text{if } l = l_1 \\ 0 & \text{otherwise} \end{cases} \quad \text{(A.3)}$$

where SB_t^k is the egg production during year t:

$$\text{SB}_t^k = \sum_l Q_l P_l N_t^{l,f,k} \quad \text{(A.4)}$$

Q_l is the fraction of females in size-class l which are mature:

$$Q_l = \begin{cases} 1 + \exp(17.18 - 0.1668 L_l) & \text{if } L_l > 64 \text{ mm} \\ 0 & \text{otherwise} \end{cases} \quad \text{(A.5)}$$

P_l is the number of eggs produced by a mature female in size-class l:

$$P_l = 0.181 L_l^{2.969} \quad \text{(A.6)}$$

f denotes the female sex, α, β are the parameters of the stock–recruitment relationship, ε_t^k the kth element of a vector generated from a multivariate normal distribution, $N(\underline{0}, \mathbf{W}_r)$, where $\mathbf{W}_r$ a variance–covariance matrix with $i - j$ elements given by $\sigma_r^2 \tau_r^{|i-j|}$ (referred to as the 'settlement residual'), σ_r the standard deviation of the logarithms of the multiplicative fluctuations in settlement, τ_r the extent of correlation between the settlement residuals for adjacent zones, and R_0^k the pre-exploitation settlement in zone k.

The values for the parameters of the stock-recruitment relationship are determined from the steepness of the stock–recruitment relationship (the fraction of virgin recruitment expected when the egg production is reduced to 20% of the pre-exploitation level; Francis (1992)). The assumption that steepness equals one (or equivalently that $\alpha = 0$ and $\beta = 1$) implies that the expected recruitment is independent of the egg production. The formulation of Eq. (A.3) is such that α and β are independent of egg production and depend only on

steepness. The values for the parameters of Eqs. (A.5) and (A.6) are based on unpublished data from the Tasmanian Aquaculture and Fisheries Institute (TAFI).

A.3. Catches

The legal catch in mass in zone k during year t, C_t^k, is assumed to be taken in a pulse in the middle of the year (i.e. after half of natural mortality), so the exploitation rate on fully selected animals in zone k due to legal fishing during year t, F_t^k, is found by using the equation:

$$F_t^k = \frac{C_t^k}{B_t^k} \tag{A.7}$$

where B_t^k is the legal fishable biomass in zone k in the middle of the year t but before fishing:

$$B_t^k = \sum_s \sum_l V^{l,s} S_{l,t}^s W_l^s N_t^{l,s,k} \, \mathrm{e}^{-M/2} \tag{A.8}$$

W_l^s is the mass of an animal of sex s and in size-class l:

$$W_l^s = a^s L_l^{b^s} \tag{A.9}$$

a^s, b^s are the parameters of the mass–length relationship (Table 5).

The legal catch in zone k during year t is calculated from the catch from all zones, C_t:

$$C_t^k = \frac{C_t q_t^k B_t^k}{\sum_{k'} q_t^{k'} B_t^{k'}} \tag{A.10}$$

where q_t^k is the catchability coefficient for zone k and year t:

$$q_t^k = \mathrm{e}^{\phi^k} \, \mathrm{e}^{\varphi_t^k}, \qquad \phi^k \sim N(0; \sigma_\phi^2) \tag{A.11}$$

σ_ϕ is the standard deviation of the variation in the logarithm of the average catchability among zones, φ_t^k the kth element of a vector generated from a multivariate normal distribution, $N(\underline{0}, \mathbf{W}_\varphi)$, where $\mathbf{W}_\varphi$ is a

Table 5
The values for the parameters of the mass-length relationship (TAFI, unpublished data)

Quantity	Females	Males
a^s	0.000271	0.000285
b^s	3.135	3.114

variance–covariance matrix with $i - j$ elements given by $\sigma_\varphi^2 \tau_\varphi^{|i-j|}$, σ_φ the standard deviation of the logarithm of the multiplicative fluctuations in catchability, and τ_φ is the extent of correlation in catchability among zones.

Eq. (A.10) is based on the assumption that fishers remove catches in proportion to catch-rate (catchability multiplied by exploitable biomass). Catchability is assumed to differ among zones and to vary inter-annually. The inter-annual variation in catchability is correlated spatially to reflect possible correlation in the environmental factors that determine catchability.

A.4. Selectivity

Gear-selectivity is assumed to be of the logistic form. This assumption has been made in some recent assessments of Australian rock lobster populations (Punt and Kennedy, 1997; Hobday and Punt, 2001) and is supported by data collected by Treble et al. (1998). Inter-annual variability in selectivity is modeled by assuming that it impacts the size at 50% selectivity:

$$S_{l,t}^s = \left(1 + \exp\left[\frac{-\ln(19)(L_l - L_{50,t}^s - \eta_t)}{D^s}\right]\right)^{-1},$$
$$\eta_t \sim N(0; \sigma_\eta^2) \tag{A.12}$$

where $L_{50,t}^s$ is the size at 50% selectivity for animals of sex s during year t:

$$L_{50,t}^s = L_{50,t-1}^s + \delta_t, \quad \delta_t \sim N(0; \sigma_\delta^2) \tag{A.13}$$

σ_η is the standard deviation of the random fluctuations in the size at 50% selectivity, σ_δ the standard deviation of the gradual changes in the size at 50% selectivity, and D^s the width of the selectivity pattern (the difference between the size at 50% and at 95% selectivity) for sex s.

The average value for the size at 50% selectivity (taken to be that for the first year included in the model) is 90 mm, and the width of selectivity pattern is 60 mm (Fig. 8 of Punt et al. (1997)).

A.5. The size-transition matrix

The entries of the size-transition matrix are determined using the equation:

$$X_{l,l'}^{s,k} = \int_{L_l-\Delta L}^{L_l+\Delta L} \frac{1}{\sqrt{2\pi}\sigma_{l'}^{s,k}}$$
$$\times e^{-((L-(\tilde{a}^{s,k}+(\tilde{b}^{s,k}+1)\bar{L}_{l'}))^2)/(2(\sigma_{l'}^{s,k})^2)}\, dL$$

$$(A.14)$$

where $\tilde{a}^{s,k}, \tilde{b}^{s,k}$ are the parameters that determine growth for sex s and zone k, and $\sigma_l^{s,k}$ is the standard deviation of the growth increment for animals of sex s in zone k in size-class l:

$$(\sigma_l^{s,k})^2 = \max[(\sigma_{\min}^{s,k})^2, \{(CV_1^{s,k})^2$$
$$+ (CV_2^{s,k})^2(\bar{L}_l)^2\}\{\tilde{a}^{s,k}+\tilde{b}^{s,k}\bar{L}_l\}^2] \quad (A.15)$$

$\sigma_{\min}^{s,k}$ is the minimum growth increment standard deviation for animals of sex s in zone k, and $CV_1^{s,k}$, $CV_2^{s,k}$ are parameters that determine the coefficient of variation of the growth increment for sex s and zone k.

A.6. Other estimated quantities

The fishable biomass in zone k in the middle of year t is defined as $B_t^k(1 - F_t^k/2)$, whereas the recruitment to the fishery at the start of year $t + 1$ is:

$$\sum_s \sum_l W_l^s S_{l,t}^s V^{l,s}\{N_{t+1}^{l,s,k} - N_t^{l,s,k}\, e^{-M}$$
$$\times (1 - F_t^k S_{l,t}^s(V^{l,s} + \Omega(1 - V^{l,s})))\} \quad (A.16)$$

A.7. Initial conditions

The initial conditions correspond to the size-structure of the population in the absence of exploitation. The pre-exploitation settlement in each zone is determined using an equation that allows pre-exploitation settlement to differ in a spatially-correlated manner, i.e.

$$R_0^k = \bar{R}_0\, e^{\mu^k} \quad (A.17)$$

where $\bar{R}_0$ is the average (across zones) pre-exploitation settlement, μ^k the kth element of a vector generated from a multivariate normal distribution, $N(\underline{0}, \mathbf{W}_\mu)$, where $\mathbf{W}_\mu$ is a variance–covariance matrix with $i - j$ elements given by $\sigma_\mu^2 \tau_\mu^{|i-j|}$, σ_μ is the standard deviation of the logarithms of the multiplicative fluctuations in the spatial distribution of the average pre-exploitation settlement, and τ_μ is the extent

of correlation in average pre-exploitation settlement between adjacent zones.

The algorithm used to determine the historical time sequence of population size for each of the 250 simulations, given a specification regarding the initial depletion of the egg production, involves first generating the values for the ε_t^k, ϕ^k, φ_t^k, η_t, ϕ_t and μ^k (Eqs. (A.3), (A.11)–(A.13) and (A.17)) and then selecting the value for $\bar{R}_0$ so that $\sum_k SB_{\text{init}}^k / \sum_{k'} SB_0^{k'}$ equals the pre-specified value.

A.8. Data generation

The data available for stock assessment purposes include catches, catch-rates, length–frequency and tag-recapture data. The length–frequency and tag-recapture data are available by year, zone and sex, and the catches and catch-rate data are available by year and zone. The catches by year and zone used by the assessment model are the legal catches (i.e. C_t^k), and the catch-rate for year t and zone k is given by $q_t^k B_t^k$. For assessments of rock lobster populations, there are often two sources of length–frequency data: samples from the landed catches and samples collected through scientific monitoring. The length–frequency of the landed catch for sex s, year t and zone k is obtained by sampling multinomially from the landed catch, i.e. size-class l is selected with probability proportional to $V^{l,s} S_{l,t}^s N_t^{l,s,k}$. The length–frequency of the scientific samples for sex s, year t and zone k is obtained by sampling multinomially with probability of selecting an animal in size-class l proportional to $S_l^s N_t^{l,s,k}$, where S_l^s is selectivity at pre-exploitation equilibrium.

The tagging data are taken to be the sizes at release and recapture of animals tagged in 1 year and recaptured the following year. These data are used when estimating the size-transition matrix. The tag-recapture data for sex s, zone k and year t are generated by first selecting the animals which were tagged and subsequently recaptured by sampling multinomially with probability of selecting an animal in size-class l proportional to $S_l^s N_t^{l,s,k}$. The observed size of a recaptured animal that was in size-class l when it was tagged is given by

$$\tilde{a}^{s,k}+(1+\tilde{b}^{s,k})L_l+\lambda, \quad \lambda \sim N(0, (\sigma_l^{s,k})^2 + \sigma_{\text{obs}}^2)$$

$$(A.18)$$

where σ_{obs} is the standard deviation of the measurement error associated with measuring a recaptured animal (assumed to be 2 mm).

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